Experts in the Neighborhood

Discussion on

“The Wisdom of the Few” *)

Christoph Pinkel

Recommender Systems
Nearest Neighbor CF

Jim

Jane

What about Kill Bill 2?
Problems

- Cold start problem
- Data sparsity
- Noise (even malicious)
- Scalability
- Privacy
The Wisdom of the Few

Classical Nearest Neighbor Collaborative Filtering

Nearest Neighbor Collaborative Filtering *with experts*
Outline

- Nearest-Neighbor Collaborative Filtering
- Proposal: “The Wisdom of the Few”
- Findings
- Measuring User Satisfaction
- Outlook & Discussion
- Conclusions
User Based Nearest Neighbor Collaborative Filtering (NN-CF)

- User similarity
- Pearson Correlation Coefficient / Cosine Similarity

\[
sim(a, b) = \frac{\sum_i (r_{ai} r_{bi})}{\sqrt{\sum_i r_{ai}^2} \sqrt{\sum_i r_{bi}^2}}
\]

\[\sum = 1 + 1 + 0\]
User Based Nearest Neighbor Collaborative Filtering (NN-CF)

- Pick **top n** neighbors
- Predicting (**top k** results)
- Weighting
  - By neighbor
  - By significance
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“The Wisdom of the Few”

- Separate experts set
- Neighbors are experts
- Bipartite graph
User Similarity

\[ \text{sim}(a, b) = \frac{\sum_i (r_{ai} r_{bi})}{\sqrt{\sum_i r_{ai}^2} \sqrt{\sum_i r_{bi}^2}} \cdot \frac{2N_{a \cup b}}{N_a + N_b} \]
Predicting Ratings

E - Experts
E’ - Neighbors
E” - With rating
Cosine
Evaluation

- Netflix data set
- Experts data set
- Showing top-k predictions
- Double evaluation
  - statistical measures (MAE)
  - user study (user satisfaction)
### Authors’ Focus

<table>
<thead>
<tr>
<th>Expert approach feasible?</th>
<th>How does this differ from traditional CF?</th>
<th>Can we avoid some pitfalls?</th>
<th>Can noise be reduced?</th>
<th>NOT: increase (technical) CF accuracy</th>
</tr>
</thead>
</table>

2/5/2010
Outline

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Evaluation – MAE

- **Mean Absolute Error (MAE)** works fine

<table>
<thead>
<tr>
<th>Method</th>
<th>MAE</th>
<th>Coverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Critics</td>
<td>0.885</td>
<td>100.0%</td>
</tr>
<tr>
<td>Expert-CF</td>
<td>0.781</td>
<td>97.7%</td>
</tr>
<tr>
<td>Neighbor-CF</td>
<td>0.704</td>
<td>92.2%</td>
</tr>
</tbody>
</table>

- Better than critics’ choice alone
- slightly worse than NN-CF
- Remember: this is not the main focus!
Targeting Problems

Traditional NN-CF
- Cold start problem
- Data sparsity
- Noise (even malicious)
- Scalability
- Privacy

“Wisdom of the Few”
- Employ experts in advance
- Change job description
- Hopefully little
- Small number of experts
- Experts are public persons
User Study

- Additional user study – rather unusual
- Focus on user satisfaction
- 100 preselected movies
- 57 participants
Satisfaction

- Nice MAE/RMSE alone are of no use
- MAE as indicator might be suboptimal
- It's all about satisfaction
- User study gets real feedback
User Study Results

![Bar Chart]

- Random
- kNN CF
- Critic's Choice
- Experts CF

Legend:
- Very Bad
- Bad
- Average
- Good
- Very Good

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Outlook & Future Work

- Generalizing for other domains
- Might want to see more studies
- Combinations with traditional CF
Strengths

- Alternative to traditional NN-CF
- Avoids several CF pitfalls
- Incredible user satisfaction – in one study
Weaknesses

- Requires experts
  - Might be too costly (economically)
  - Or even impossible
- No more precise than baseline
- Currently very domain specific
- User study is not a conclusive proof
Conclusion

- CF – Recommendations
  - Issues to traditional CF (like noise)
- Expert neighbors
  - Partially solve issues
- Approach works
- Great user satisfaction (user study)
- Domain-specific, need experts

Thank you! Questions?